Assessing Spatial Patterns of Crime in Smaller Communities

Alan T. Murray

William V. Ackerman

Department of Geography
Ohio State University
Columbus, OH 43210

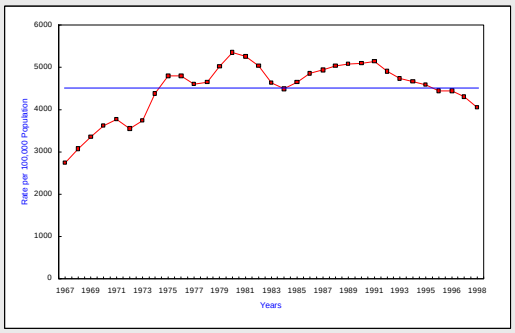
Email: murray.308@osu.edu

Related Published Work

- Murray, A., I. McGuffog, J. Western and P. Mullins (2001). "Exploratory spatial data analysis techniques for examining urban crime." *British Journal of Criminology* **41**, in press.
- Ackerman, W. (1998). "Socioeconomic correlates of increasing crime rates in smaller communities." *The Professional Geographer* **50**, 372-387.
- Ackerman, W. (1998). "The spread of crime to smaller Ohio cities and the spatial distribution of crime in Lima, Ohio." *The Justice Professional* **10**, 265-289.
- Ackerman, W. (2000). "The concept of community policing and a case study of Lima, Ohio." In *Atlas of Crime: Mapping the Criminal Landscape*, edited by L. Turnbull, E. Hendrix and B. Dent (Phoenix: Oryx Press).

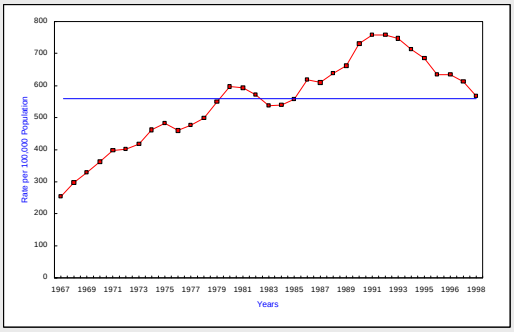
Why should we be interested in smaller cities?

Property Crime in the U.S.



Federal Bureau of Investigation, Uniform Crime Reports 1967-1998

Violent Crime in the U.S.



Federal Bureau of Investigation, Uniform Crime Reports 1967-1998

Crime in Smaller Communities

- Rates of crime increased dramatically in smaller cities during the 1980s
- Little research work done examining crime in smaller cities
- Change by city size (1977-1988):

	Population		
	< 100,000	100,000-500,000	> 500,000
Reported Violent Crime	67.5	41.6	19.9
Reported Property Crime	12.9	8.7	7.0
Impoverished Families	27.1	14.3	25.6
Unemployment	126.5	10.4	91.4

Ackerman, W. (1998). "The spread of crime to smaller Ohio cities ..." The Justice Professional, vol. 10, 265-289

In Ohio

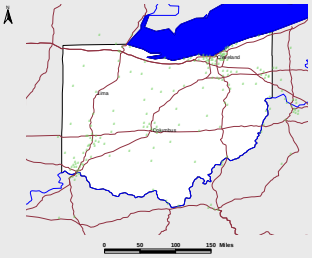
Mean crime rates by city size for 1985-1993 (and % change from 1976-1984) per 50,000:

City	Violent (% change)	Property (% change)
Columbus	500.8 (34.6%)	4050.3 (2.7%)
Cleveland	732.0 (-11.7%)	3400.1 (-10.6%)
Cincinnati	549.5 (17.9%)	3330.6 (-9.3%)
Toledo	421.1 (11.4%)	3837.1 (-4.9%)
Akron	509.8 (86.5%)	3250.7 (-3.8%)
Dayton	784.0 (-2.1%)	4553.9 (-15.6%)
Youngstown	696.3 (42.9%)	3008.5 (-7.2%)
Canton	701.3 (116.9%)	3083.1 (1.9%)
Springfield	756.7 (135.5%)	3621.4 (14.6%)
Mansfield	817.1 (35.4%)	3585.0 (0.9%)
Lima	774.3 (108.9%)	3623.1 (-15.9%)

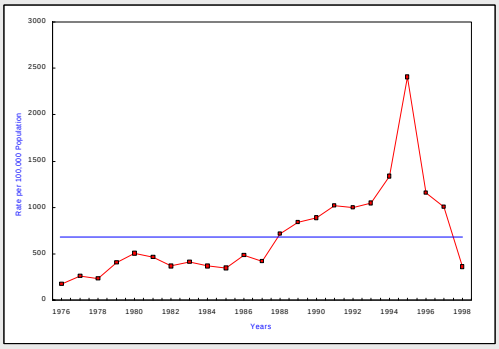
Ackerman, W. (1998). "The spread of crime to smaller Ohio cities ..." The Justice Professional, vol. 10, 265-289

Lima, Ohio

- Approximately 42,000 people
  - ✓ >25% African American
- Substantial job losses due to deindustrialization in 70s and 80s
  - ✓ 15,000 jobs lost (military, steel, aerospace)
- Increased levels of poverty, unemployment and crime
  - ✓ >20% of population at or below poverty level
  - ✓ Increased concentration of female head of households



Violent Crime in Lima, Ohio



Federal Bureau of Investigation, Uniform Crime Reports 1976-1998

Police Force in Lima

- Chief Greg Garlock
- Approximately 93 officers and detectives
- No computers in patrol cars
- 17% increase in crime so far in 2000
- Tiburon system utilized for reporting and managing reported crime events
  - – Unix based

Why look for spatial patterns?

Areas of Crime Research

1. Ecology of crime (environmental criminology)
   physical design characteristics - preventing or encouraging crime
2. Social ecological
   social processes - creating a criminogenic social environment
3. Crime mapping
   display of crime events
4. Crime analysis
   establishing crime activity relationships - patterns

Murray et al. (2001). "Exploratory spatial data analysis techniques for examining urban crime." British Journal of Criminology 41, in press.

Spatial Analysis of Crime

- Crime and other information
- Integration of spatial information layers
- Exploratory analysis
  - Cartographic display
  - Optimization based clustering
  - Spatial statistical analysis

Spatial Information

- Census data
  - socio-demographic information - population, age, occupation, education, income, household size, employment, rent, religion, number of vehicles, etc.
- Transportation
  - main roads
- Parks
- Water bodies

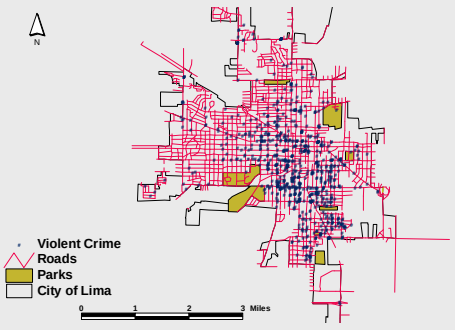
Integration of Spatial Layers

- Incident location
- Block and block group - spatial reporting units utilized from the US Census
- Proximity analysis - minimum distance from areas to roads, parks, lakes
- Spatial containment - number of crimes in a geographic area

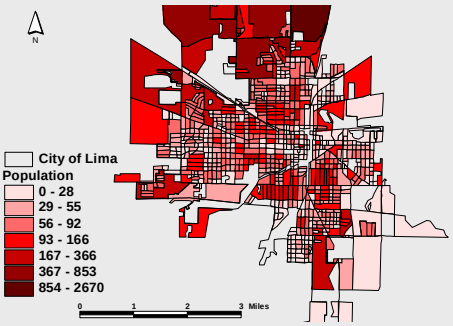
Exploratory Analysis

- Visual investigation – Crime mapping software or commercial Geographic Information Systems (GIS)
- Spatial modeling (spatial data mining) - Cluster analysis software or GIS extensions
- Spatial statistical analysis – Statistical packages or GIS extensions

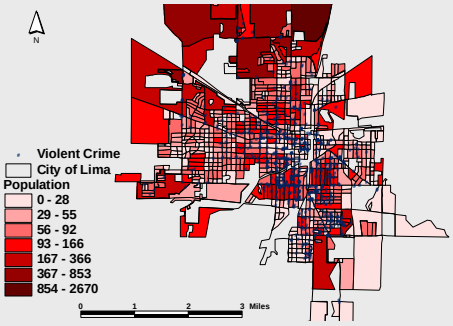
Violent Crime in Lima



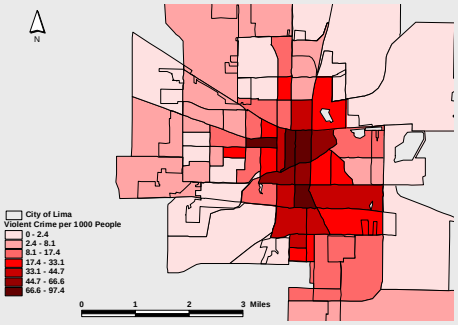
Population in the City of Lima



Crime and Population



Block Group Crime Rates



Choropleth Mapping

- Map display important medium for summarizing information & geographic relationships
- Standard feature of commercial geographical information system packages
- Substantial research devoted to choropleth mapping over the past 50 years
- Goal - effective methods for depicting differences in the attribute being displayed

Murray, A. and Shyy, T. (2000). "Integrating attribute and space characteristics in choropleth display and spatial data mining." International Journal of Geographical Information Science 14, 649-667

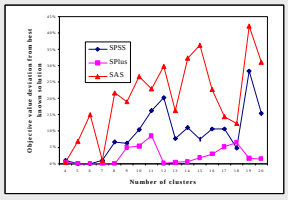
Attribute Display Approaches

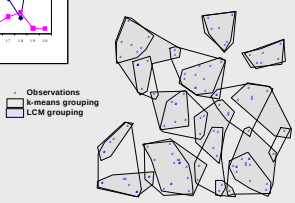
1. Constant series classes
   - equal intervals
   - standard deviations
   - quantiles
   - equal areas
2. Systematically unequal classes
   - arithmetic progression
   - geometric progression
3. Irregular classes
   - exogenous
   - natural breaks

Spatial Patterns

- Optimization based clustering techniques widely utilized
  - k-means approach - minimizing total within group variance
  - Median - minimizing total within group difference
- Problems associated with k-means approaches
  - Optimality
  - Bias
- Various approaches possible for incorporating spatial influences

Problematic Aspects of k-means





Murray, A. and Grubesic, T. (2000). "Identifying non-hierarchical spatial clusters." Submitted for review.

Difference Measures

Spatial component

$$d_{ij} = \left(\left| \tilde{x}_i - \tilde{x}_j \right|^m + \left| \tilde{y}_i - \tilde{y}_j \right|^m \right)^{1/m}$$

$(\tilde{x}_i, \tilde{y}_i)$ = coordinates of observation i

m = distance metric parameter

Attribute component

$$a_{ij} = \sum_k l_k \left| f_{ik} - f_{jk} \right|$$

l_k = weight associated with attribute k

f_{ik} = value of attribute k for observation i

$\sum_k l_k = 1$

Attribute and Space Median Classification

Minimize

$$Z = w_a \sum_i \sum_j a_{ij} z_{ij} + w_d \sum_i \sum_j d_{ij} z_{ij}$$

Subject to

(1) $\sum_j z_{ij} = 1 \quad \forall i$

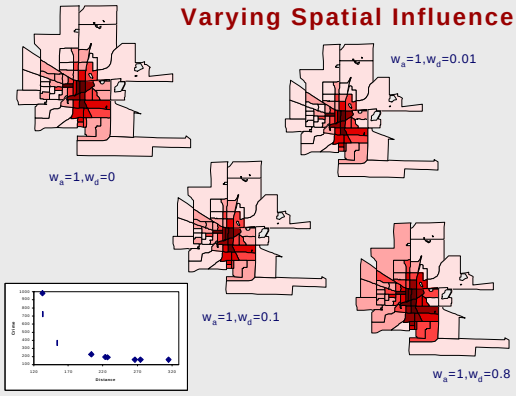
(2) $z_{ij} \leq x_j \quad \forall i, j$

(3) $\sum_j x_j = p$

(4) $z_{ij} = (0,1) \quad \forall i, j$

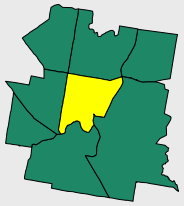
$x_j = (0,1) \quad \forall j$

Varying Spatial Influence



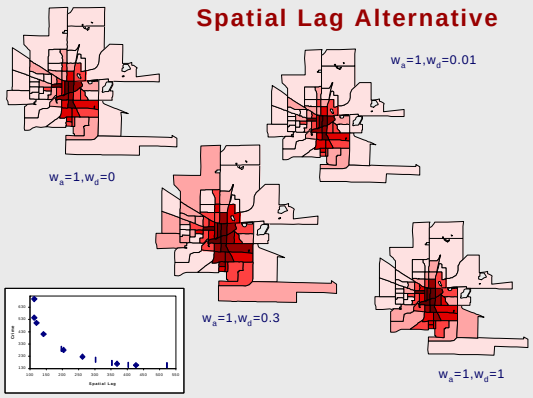
Spatial Lag

$$l_i = \frac{\sum_{j \in N_i} f_j}{|N_i|}$$

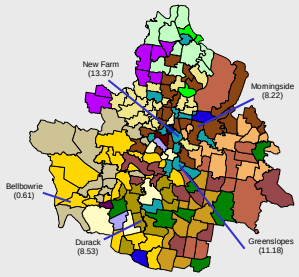


Murray, A.(2000). "Spatially lagged choropleth display." Proceedings of 9th International Symposium on Spatial Data Handling, edited by P. Forer, A. Yeh and J. He, 1a40-49 (Beijing: International Geographical Union).

Spatial Lag Alternative



Twenty-one Spatial Clusters



Direct Application to Point-based Incidents by Time

Variation in interpretation and meaning

Spatial Statistical Analysis

- Box map
- Moran's I
- Moran scatterplot
- Local indicators of spatial association
- Multivariate linear regression

Issues for Crime Analysis

- Not clear how optimization based clustering approaches should be utilized
  - What is the appropriate number of clusters?
  - How should distance be weighted?
  - Where are the hot/cold spots?
- How do clustering approaches relate to local statistics?

Conclusions

- GIS and Spatial Models
  - Enhance our ability to study and understand patterns of crime
  - Visualization
- Smaller cities
  - Need for focused research
  - Numerous technological issues
  - Scale of analysis
- Academic and police department collaboration essential
  - Especially for smaller cities
  - But … needs and goals of analysis typically differs